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## **FOREIGN EXCHANGE: MACRO PUZZLES, MICRO TOOLS**

**Richard K. Lyons**

Haas School of Business  
University of California, Berkeley  
and

Visiting Scholar

Center for Pacific Basin Monetary and Economic Studies  
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**Center for Pacific Basin Monetary and Economic Studies  
Economic Research Department  
Federal Reserve Bank of San Francisco  
101 Market Street  
San Francisco, CA 94105-1579  
Tel: (415) 974-3184  
Fax: (415) 974-2168  
<http://www.frbsf.org>**

# Foreign Exchange: Macro Puzzles, Micro Tools

Richard K. Lyons\*

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## Abstract

This paper reviews recent progress in applying information-theoretic tools to long-standing exchange rate puzzles. I begin by distinguishing the traditional public information approach (e.g., monetary models, including new open-economy models) from the newer dispersed information approach. (The latter focuses on how information is aggregated in the trading process.) I then review empirical results from the dispersed information approach and relate them to two key puzzles, the determination puzzle and the excess volatility puzzle. The dispersed information approach has made progress on both.

## Correspondence

Richard K. Lyons  
Haas School of Business, U.C. Berkeley  
Berkeley, CA 94720-1900  
Tel: 510-642-1059, Fax: 510-643-1420  
lyons@haas.berkeley.edu

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# Foreign Exchange: Macro Puzzles, Micro Tools

To repeat a central fact of life, there is remarkably little evidence that macroeconomic variables have consistent strong effects on floating exchange rates, except during extraordinary circumstances such as hyperinflations. Such negative findings have led the profession to a certain degree of pessimism vis-à-vis exchange-rate research.

Frankel and Rose (1995)

Does the foreign exchange market aggregate information? Surely it does: so many of the variables that drive pricing are dispersed throughout the economy (e.g., individuals' risk preferences, firms' productivities, individuals' money demands, individuals' hedging demands, etc.). Indeed, aggregating dispersed information is one of asset markets' central functions.<sup>1</sup> Yet models of exchange rate determination abstract completely from information aggregation. These models (e.g., monetary models, portfolio balance models, new open-economy macro models) posit an information environment in which all relevant information is publicly known. This approach is sensible if the abstraction misses little, i.e., if dispersed information is rapidly summarized in the public macro variables we rely on to estimate our models. Only recently has this common assumption received any attention.

My thesis is that abstracting from information aggregation when analyzing exchange rates misses quite a lot. The argument rests on two main points. First, empirically the public information approach fares poorly (see, e.g., Meese and Rogoff 1983 and the surveys by Frankel and Rose 1995 and Taylor 1995). Meese (1990) describes the explanatory power of these models (for monthly or quarterly exchange rates) as “essentially zero.” More recent models within this approach also fare poorly (Bergin 2001). In sum, there is general agreement that the public information approach is deficient; the open question is why.

My second main point is more positive: recent empirical work on exchange rates using what I call the “dispersed information approach” has enjoyed some success. This work relies on micro models of how, specifically, asset markets accomplish information aggregation. When coupled with the poor performance of public information models, these positive results imply that the above assumption—that dispersed information is rapidly summarized in public information—is dubious.

The remainder of this article focuses on positive results from the dispersed information approach and relates them to fundamental exchange rate puzzles. Section 1 provides an overview of order flow as an information aggregator. Section 2 addresses the determination puzzle—why the explanatory power of concurrent macro variables is so low. Section 3 addresses the excess volatility puzzle—why floating rates are more volatile than measured fundamentals predict. Section 4 concludes by providing directions for further research.

## 1. Order Flow: An Information Aggregator

### Introduction and Definition

When one moves from the public information approach to the dispersed information approach, a variable that plays no role in the former takes center stage: order flow. Order flow is a term from the field of micro-

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<sup>1</sup> Nobel laureate Friedrich Hayek (1945) provides an early and powerful articulation of this point: “the problem of rational economic order is determined precisely by the fact that knowledge of the circumstances of which we must make use never exists in concentrated or integrated form, but solely as dispersed bits of incomplete and frequently contradictory knowledge which all the separate individuals possess. The economic problem of society is thus a problem of the utilization of knowledge not given to anyone in its totality.”

structure finance.<sup>2</sup> Understanding it is essential for appreciating how the dispersed information approach departs from the public information approach. Order flow is transaction volume that is *signed* (making it quite different from conventional, unsigned volume). For example, if you approach a dealer (marketmaker), and you decide to sell the dealer 10 units (shares, euros, etc.), then transaction volume is 10, but order flow is –10. Order flow takes a negative sign because you—the initiator of this transaction—are on the sell side. The quoting dealer is on the passive side.<sup>3</sup> (Trades are signed according to the active, or initiating side.) Over time, order flow is measured as the sum of signed buyer-initiated and seller-initiated orders. A negative sum means net selling over the period.

Order flow is a variant of another important term, “excess demand.” It is a variant rather than a synonym for two reasons, the first relating to the excess part and the second relating to the demand part. For the former, note that excess demand equals zero in equilibrium by definition—there are two sides to every transaction. This is not of true order flow: in markets organized like foreign exchange, orders are initiated against a marketmaker, who (if properly compensated) stands ready to absorb imbalances between buyers and sellers. These “uninitiated” trades of the marketmaker drive a wedge between the two concepts, excess demand and order flow.<sup>4</sup> The second reason the concepts differ is that order flow is in fact distinct from demand itself. Order flow measures actual transactions, whereas demand shifts need not induce transactions. For example, the demand shifts that move price in traditional exchange rate models (e.g., monetary models) are caused by the flow of public information, which moves rates without transactions ever needing to occur.

Consider a simple diagram that illustrates an important feature of dispersed information models that relates directly to order flow (see figure 1). The diagram shows that information processing has two stages. The first stage is the analysis or observation of dispersed fundamentals by non-dealer market participants (mutual funds, hedge funds, individuals with special information, etc.). The second stage is the dealer’s—i.e., the price setter’s—interpretation of the first-stage analysis. The dealer’s interpretation comes from reading the order flow. Dealers set price on the basis of this reading.

Order flow conveys information about dispersed fundamentals because it contains the trades of those who analyze/observe those fundamentals. It is a transmission mechanism. Naturally, though, these informative trades may be mixed with uninformative trades, making the task of “vote counting” rather complex. In some dispersed information models, the dealer learns nothing about fundamentals that she does not learn from order flow. As a practical matter, this is clearly too strong. The dealer’s dependence on learning only from order flow arises in some models because all of the relevant information is dispersed. When information is publicly known, dealers do not need to learn from order flow. In practice, though some information relevant to FX is publicly known, some is not, so learning from order flow can be important. The empirical models I describe in section 2 admit both possibilities.

Consider such a “hybrid” model from a graphical perspective. The top panel of figure 2 illustrates the connection between fundamentals and price under the public information approach. Under this approach, not only is information about fundamentals publicly known, so too is the mapping from that information to price. Consequently, price adjustment is direct and immediate. The middle panel shows the dispersed information approach. The focus in that case is on fundamental information that is not publicly known. In those models,

<sup>2</sup> Microstructure finance has two main strands: market design and information processing. The dispersed information approach to exchange rates borrows heavily from the second of these strands.

<sup>3</sup> Measuring order flow is slightly different when trading takes place via a “limit order book” rather than through dealers. (An example of a limit order is “buy 10 units for me if the market reaches a price of 50.”) Limit orders are collected in an electronic “book” and the most competitive of those orders define the best available bid and offer prices. When measuring order flow, limit orders are the passive side of any transaction, just as the quoting dealer is always on the passive side when trading involves dealers. When orders arrive that require immediate execution (e.g., an order to “sell 10 units now at the best available price), these orders—called market orders—generate the signed order flow.

<sup>4</sup> In rational expectations (RE) models of trading, order flow is undefined because all transactions in that setting are symmetric. One might conclude from RE models that one could never usefully distinguish the “sign” of a trade between two willing counterparties. A large empirical literature in microstructure finance suggests otherwise (Lyons 2001).

information is first transformed into order flow. This order flow becomes a signal to the price setter that price needs to be adjusted. The bottom panel presents the hybrid view. Here, the model accommodates both possibilities: information that affects price directly and information that affects price via order flow. With models that allow for both, the data can determine their relative importance.

## **Order Flow and Exchange Rates Over Long Horizons**

It is common to associate “microstructure analysis” with “high frequency.” The association is natural, but deceptive. It is true that empirical work in microstructure finance is generally high frequency. But this does not imply that microstructure tools are irrelevant to lower-frequency, resource relevant phenomena. Indeed, there are ample tools within the micro approach for addressing lower-frequency phenomena. And new tools continue to emerge, thanks in part to recognition within the broader microstructure literature that resource allocation warrants greater attention.

Regarding long-lived effects, the most important point to recognize is that when order flow conveys information, its effect on price *should* be long-lived. Indeed, a common assumption in empirical work for distinguishing information from pricing errors is that information’s effects on price are permanent, whereas pricing errors are transitory (French and Roll 1986, Hasbrouck 1991). These long-lived effects are borne out in the data, in equity markets, bond markets, and FX markets. In FX, for example, Evans (1997), Evans and Lyons (1999), Payne (1999), and Rime (2000) show that order flow has significant effects on exchange rates that persist. Indeed, statistically these effects appear to be permanent. Among microstructure’s long-lived implications, this “information” channel is definitely the most fundamental.

An analogy may be helpful. The dispersed information approach may speak to longer-horizon exchange rates in much the same way that microscopes speak to pathologies with macro impact. In medicine, microscopes provide resolution at the appropriate level—the level at which the phenomenon emerges. This is true irrespective of whether the phenomenon also has macro impact. Resolution at this level is the key to our understanding. Similarly, tools from the dispersed information approach provide resolution at the level where its “phenomenon” emerges—the level where price is determined. What information do dealers have available to them, and what are the forces that influence their pricing decisions? (Whether we like it or not, it is a stubborn fact that in the major currency markets, *there is no exchange rate other than the price these people set.*) Answering these questions does indeed help explain exchange rates over longer horizons, as the next section shows.

## **Applying Microstructure Tools to Exchange Rate Puzzles**

What about the big puzzles in exchange-rate economics? Two of the biggest puzzles are:<sup>5</sup>

- [1] **The determination puzzle:** exchange-rate movements are virtually unrelated to macroeconomic fundamentals (at least over periods of less than about two years); and
- [2] **The excess volatility puzzle:** exchange rates are excessively volatile relative to our best measures of fundamentals;

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<sup>5</sup> Within international finance more broadly, there are four main puzzles, the two listed plus the “forward bias” and “home bias” puzzles. (Forward bias refers to conditional bias in forward exchange rates, whereas home bias refers to investors under-investing internationally.) For applications of the dispersed information approach to these other puzzles see Lyons (2001). These three exchange-rate puzzles have analogues in other markets. For equities, papers recognizing the three puzzles include Roll (1988), Shiller (1981), and Mehra and Prescott (1985), respectively. (However, the equity-market version of the forward bias puzzle—the so-called equity premium puzzle—is a much looser analogue than the other two: the large risk premium on equity is rather stable over time and remains positive, whereas the large risk premium in FX changes over time, including frequent changes in sign.) Microstructure tools are just beginning to be applied to those major equity puzzles (see, for example, Easley et al. 1999).

The dispersed information approach links these puzzles to one-another, the link being expectations formation—i.e., how market participants form their expectations of future fundamentals. It makes this link without departing from rational expectations. Rather, the microstructure approach grounds expectations formation more directly in a richer, information-economic setting. The focus is on information *types* (such as public versus dispersed) and *how* information maps into expectations (e.g., whether the aggregation of order flow “votes” is efficient). The issues of information type and mapping to expectations are precisely where tools from microstructure finance provide resolving power.<sup>6</sup>

## **A First Look at the Data**

Figure 3 provides a convenient summary of order flow’s explanatory power. The solid lines represent the spot rates of the DM and yen against the dollar over the four-month sample of the Evans (1997) dataset. The dashed lines represent cumulative order flow for the respective currencies over the same period. Order flow, denoted by  $X$ , is the sum of signed trades (starting from the beginning of the sample) between foreign exchange dealers worldwide.<sup>7</sup> Cumulative order flow and nominal exchange-rate levels are strongly positively correlated (price increases with buying pressure). This result is intriguing. Order flow appears to matter for exchange-rate determination, and the effect appears to persist (otherwise the exchange rate’s level would reflect only concurrent or very recent order flow and not *cumulative* order flow). This persistence is an important property, one that I examine more closely below. For order flow to be helpful in resolving big exchange-rate puzzles, its effects have to persist over horizons that match those puzzles (monthly, at a minimum).<sup>8</sup>

## **2. The Determination Puzzle**

This section and the next examine traditional exchange rate puzzles, showing how tools from microstructure finance are used to address them. They are not intended to put these puzzles to rest: the puzzles wouldn’t be traditional if they weren’t stubborn. My intent is to provide a sense for how to address macro issues by looking under the “micro lamppost.”

As noted, the proportion of monthly exchange rate changes our textbook models can explain is essentially zero. In their survey, Frankel and Rose (1995) summarize as follows:<sup>9</sup>

The Meese and Rogoff analysis at short horizons has never been convincingly overturned or explained. It continues to exert a pessimistic effect on the field of empirical exchange rate modeling in particular and international finance in general ... such results indicate that no model based on such standard fundamentals like money supplies, real income, interest rates, inflation rates, and current account balances will ever succeed in explaining or predicting a

<sup>6</sup> Of course, the dispersed information approach also has its drawbacks, an important one being the lack of publicly available order flow data over long periods.

<sup>7</sup> Because the Evans (1997) data set does not include the size of every trade, this measure of order flow is in fact the *number* of buys minus sells. That is, if a dealer initiates a trade against another dealer’s DM/\$ quote, and that trade is a \$ purchase (sale), then order flow is +1 (–1). These are cumulated across dealers over each 24-hour trading day (weekend trading—which is minimal—is included in Monday).

<sup>8</sup> Readers familiar with the concept of co-integration will recognize that it offers a natural means of testing for a long-run relationship. In section 3 I present evidence that cumulative order flow and the level of the exchange rate are indeed cointegrated, indicating that the relationship between order flow and price is not limited to high frequencies. I also show in that section why a long-run relationship of this kind is what one should expect.

<sup>9</sup> At longer horizons, e.g., longer than two years, macro models begin to dominate the random walk (e.g., Chinn 1991 and Mark 1995). But exchange-rate determination remains a puzzle at horizons less than two years (except in cases of hyperinflation, in which case the inflation differential asserts itself as a driving factor, in the spirit of PPP).

high percentage of the variation in the exchange rate, at least at short- or medium-term frequencies.

This is the determination puzzle. Immense effort has been expended to resolve it.<sup>10</sup>

If determinants are not macro fundamentals like interest rates, money supplies, and trade balances, then what are they? Two alternatives have attracted a lot of attention among macroeconomists. The first is that exchange-rate determinants include extraneous variables. These extraneous variables are typically modeled as speculative bubbles. (A bubble is a component of an asset's price that is non-fundamental. A bubble can cause price to rise so fast that investors are induced to buy, even though the bubble may burst at any time; see, e.g., Meese 1986 and Evans 1986.) On the whole, however, the empirical evidence on bubbles is not supportive: in their survey, Flood and Hodrick (1990) conclude that the existing evidence is unconvincing. A second alternative to macro fundamentals is irrationality. For example, exchange rates may be determined, in part, from avoidable expectational errors (Dominguez 1986, Frankel and Froot 1987, and Hau 1998). On *a priori* grounds, many financial economists find this second alternative unappealing. Even if one is sympathetic, however, there is a wide gulf between the presence of irrationality and accounting for exchange rates empirically.<sup>11</sup>

This section addresses the determination puzzle using the dispersed information approach, drawing heavily from work presented in Evans and Lyons (1999). One advantage of this approach is that it directs attention to variables that have escaped the attention of macroeconomists. A telling quote along these lines appears in Meese (1990):

Omitted variables is another possible explanation for the lack of explanatory power in asset market models. However, empirical researchers have shown considerable imagination in their specification searches, so it is not easy to think of variables that have escaped consideration in an exchange-rate equation.

Among the variables escaping consideration, order flow may be the most important.

### **A Hybrid Model with Both Macro and Micro Determinants**

To establish a link between the micro and macro approaches, figure 2 introduced a “hybrid” model with components from both. The hybrid model in that figure could be written as follows:

$$(1) \quad \Delta P_t = f(i, m, z) + g(X, I, Z) + \varepsilon_t.$$

where the function  $f(i, m, z)$  is the macro component of the model and  $g(X, I, Z)$  is the microstructure component. The driving variables in the function  $f(i, m, z)$  include current and past values of home and foreign nominal interest rates  $i$ , money supply  $m$ , and other macro determinants, denoted here by  $z$ . The driving variables in the function  $g(X, I, Z)$  include order flow  $X$  (signed so as to indicate direction), a measure of dealer net positions (or inventory)  $I$ , and other micro determinants, denoted by  $Z$ . An important take-away from the relevant literatures is that  $f(i, m, z)$  and  $g(X, I, Z)$  depend on more than just current and past values of their determinants—they also depend, crucially, on expectations of determinants' future

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<sup>10</sup> The determination puzzle exists in equity markets as well—see Roll (1988). Roll can account for only 20% of daily stock returns using traditional equity fundamentals, a result he describes as a “significant challenge to our science.”

<sup>11</sup> Another alternative to traditional macro modeling is the recent “new open-economy macro” approach (e.g., Obstfeld and Rogoff 1995). I do not address this alternative here because, as yet, the approach has not produced empirical exchange-rate equations that alter the Meese-Rogoff (1983) conclusions (see Bergin 2001).



values. This stands to reason: rational markets are forward looking, so these expectations are important for setting prices today.

Though I have split this stylized hybrid model into two parts, the two parts are not necessarily independent. This will depend on the main micro determinant—order flow  $X$ —and the type of information it conveys. In fact, order flow conveys two main information types: *payoff information* and *discount-rate information*. In macro models, information about future payoffs translates to information about future  $(i, m, z)$ . One way order flow can convey information about future  $(i, m, z)$  is by aggregating the information in people's expectations of  $(i, m, z)$ . (Recall that as a measure of expectations, order flow reflects people's willingness to back their beliefs with money; and like actual expectations, this measure evolves rapidly, in contrast to measures derived from macro data.) To fix ideas, write the price of foreign exchange,  $P_t$ , in the standard way as a function of current and expected future macro fundamentals:  $P_t = g(f_t, f_{t+1}^e)$ . In dispersed information models, price-setters learn about changes in  $f_{t+1}^e$  by observing order flow. Thus, when order flow conveys payoff information, macro and micro determinants are interdependent: order flow acts as a proximate determinant of price, but standard macro fundamentals are the underlying determinant.<sup>12</sup>

If order flow  $X$  conveys discount-rate information only, then the two sets of determinants  $(i, m, z)$  and  $(X, I, Z)$  can indeed be independent. To understand why, suppose the discount-rate information conveyed by order flow  $X$  is about portfolio-balance effects (e.g., persistent changes in discount rates, due to changing risk preferences, changing hedging demands, or changing liquidity demands under imperfect substitutability).<sup>13</sup> Now, consider the two monetary macro models (flexible and sticky-price). Portfolio-balance effects from order flow  $X$  are unrelated to these models' specifications of  $f(i, m, z)$ . This is because the monetary models assume that different-currency assets are perfect substitutes (i.e., they assume that Uncovered Interest Parity holds: assets differing only in their currency denomination have the same expected return). Thus, effects from imperfect substitutability are necessarily independent of the  $f(i, m, z)$  of these monetary models. In the case of the macro portfolio-balance model, in contrast, portfolio-balance effects from order flow  $X$  are quite likely to be related to the determining variables  $(i, m, z)$ . Indeed, in that model, price effects from imperfect substitutability are the focus of  $f(i, m, z)$ .

Before describing the hybrid model estimated by Evans and Lyons (1999), let me address some front-end considerations in modeling strategy. First, the determination puzzle concerns exchange-rate behavior over months and years, not minutes. Yet most empirical work in microstructure finance is estimated at the transaction frequency. The first order of business is to design a trading model that makes sense at lower frequencies. Several features of the Evans-Lyons model contribute to this (as will be noted specifically below, as the features are presented). Second, because interdealer flow is more transparent, it is more immediately relevant to FX price determination than customer-dealer order flow. The hybrid model should reflect this important institutional feature. Third, the model should provide a vehicle for understanding the behavior of interdealer order flow in figure 3. That figure presents cumulative interdealer flow in the \$/DM and \$/Yen markets over the four-month Evans (1997) data set, the same data set used by Evans and Lyons (1999). A puzzling feature is the persistence: there is no obvious evidence of mean reversion in cumulative order flow. How can this be consistent with the fact that individual dealer inventories have a very short half-life (i.e., their positions revert to zero rapidly)? The Evans-Lyons model accounts for this seeming incongruity.

<sup>12</sup> If order flow is an informative measure of macro expectations, then it should forecast surprises in important variables (like interest rates). New order-flow data sets that cover up to six years of FX trading—such as the data set examined by Fan and Lyons (2001)—provide enough statistical power to test this. The Evans (1997) data set used by Evans and Lyons (1999) is only four months, so they are not able to push in this direction.

<sup>13</sup> Lyons (2001) introduces two sub-categories of discount-rate information: information about inventory effects and information about portfolio-balance effects. I do not consider information about inventory effects here because inventory effects are transitory, and are therefore unlikely to be relevant for longer-horizon macro puzzles.

## The Evans-Lyons Model

Consider an infinitely-lived, pure-exchange economy with two assets, one riskless, and one with stochastic payoffs representing foreign exchange. The periodic payoff on foreign exchange, denoted  $R_t$ , is composed of a series of increments, so that

$$(2) \quad R_t = \sum_{i=1}^t \Delta R_i$$

The increments  $\Delta R_t$  are i.i.d.  $\text{Normal}(0, \mathbf{S}_R^2)$  and represent the flow of public macroeconomic information—the macro component of the model  $f(i, m, z)$ . For concreteness, one can think of this abstract payoff increment  $\Delta R_t$  as changes in interest rates. Periodic payoffs are realized at the beginning of each day.

The foreign exchange market is organized as a decentralized dealership market with  $N$  dealers, indexed by  $i$ , and a continuum of non-dealer customers (the public), indexed by  $z \in [0, 1]$ . Within each period (day) there are three rounds of trading:

Round 1: dealers trade with the public.

Round 2: dealers trade among themselves to share risk.

Round 3: dealers trade again with the public to share risk more broadly.

The timing within each day is summarized in Figure 4. Dealers and customers all have identical negative exponential utility (constant absolute risk aversion).

Per Figure 4, after observing  $R_t$  each dealer sets a quote for his public customers. These quotes are scalar two-way prices, set simultaneously and independently.<sup>14</sup> Denote this dealer  $i$  quote in round 1 of day  $t$  as  $P_{it}^1$ . Evans and Lyons show that, in equilibrium, all dealers choose to quote the same price, denoted  $P_t^1$  (implied by no arbitrage). Each dealer then receives a customer-order realization  $C_{it}^1$  that is executed at his quoted price  $P_t^1$ , where  $C_{it}^1 < 0$  denotes a customer sale (dealer  $i$  purchase). Each of these  $N$  customer-order realizations is distributed

$$(3) \quad C_{it}^1 \sim \text{Normal}(0, \mathbf{S}_C^2)$$

and they are uncorrelated across dealers. Importantly, the  $C_{it}^1$  realizations are not publicly observable. For later discussion of the model's intuition, it is useful to define the aggregate public demand in round 1 as the sum of the customer orders received by the  $N$  dealers:

$$(4) \quad C_t^1 = \sum_{i=1}^N C_{it}^1$$

One important choice in specifying the model is the correlation between customer orders  $C_{it}^1$  and the stream of payoff increments  $\Delta R_t$ . This choice determines whether the macro and micro components of the model—the  $f(i, m, z)$  and  $g(X, I, Z)$ —are interdependent. If there is no correlation, it is not possible for order flow to convey payoff information. Because Evans and Lyons (1999) have only four months of order flow data, they are unable to determine empirically whether order flow conveys payoff information, discount-rate information, or both. Because of this, they choose to model the customer orders  $C_{it}^1$  as distributed independently of the payoff stream  $R_t$ —arguably, a less controversial choice. This means that, in their model, the only kind of information that order flow can convey is discount-rate information. And because their

<sup>14</sup> Introducing a bid-offer spread (or price schedule) in round one to endogenize the number of dealers is a straightforward extension.

model rules out inventory effects at the daily frequency (as we shall see below), the discount-rate information in their model corresponds to what macroeconomists call portfolio balance effects.

Round 2 is the interdealer trading round. Each dealer simultaneously and independently quotes a scalar two-way price to other dealers  $P_{it}^2$ . These interdealer quotes are observable and available to all dealers in the market. Evans and Lyons show that, like in round 1, all dealers choose to quote the same price, denoted  $P_t^2$ . Each dealer then simultaneously and independently trades on other dealers' quotes. (Orders at a given price are split evenly across any dealers quoting that price.) Let  $T_{it}$  denote the (net) interdealer trade initiated by dealer  $i$  in round 2 of day  $t$ .

Importantly, at the close of round 2 all dealers observe the order flow from interdealer trading that day:

$$(5) \quad X_t = \sum_{i=1}^N T_{it}$$

This order-flow information is important to the model because it conveys the size and sign of the public order flow in round 1. To understand why, consider the interdealer trading rule derived by Evans and Lyons:

$$(6) \quad T_{it} = \alpha C_{it}^1$$

where  $\alpha$  is a constant coefficient. Each dealer's trade in round 2 is proportional to the customer order he receives in round 1. This implies that when dealers observe the interdealer order flow  $X_t = \sum_i T_{it} = \alpha C_t^1$ , they can infer the aggregate public order flow  $C_t^1$  in round 1.

In round 3, dealers share overnight risk with the non-dealer public. This feature is important in distinguishing this model from models focused on intraday trading. Unlike round 1, the public's trading in round 3 is non-stochastic. To start the round, each dealer simultaneously and independently quotes a scalar two-way price  $P_t^3$  (also common across dealers). These quotes are observable and available to the public at large.

A crucial assumption made by Evans and Lyons is that dealers set prices in round 3 such that the public willingly absorbs all dealer inventory imbalances, so that each dealer ends the day with no net position.<sup>15</sup> As an empirical matter, it is common practice for FX dealers to end each day with no net position, and this squares with the empirical findings (Lyons 1995, Yao 1998). Note too that this assumption rules out inventory effects on price at the daily frequency (because dealers do not hold overnight positions that require compensation). The round-3 price that dealers actually quote to induce public absorption of these imbalances depends on the round-2 interdealer order flow  $X_t$ : this interdealer order flow informs dealers of the size of the total position that the public needs to absorb (as noted,  $X_t = \alpha C_t^1$ ).

More precisely, to determine the round-3 price, dealers need to know two things: the total position that the public needs to absorb (which they learn from  $X_t$ ), and the public's risk-bearing capacity. Regarding the latter, the public's capacity for bearing foreign-exchange risk is assumed less than infinite (i.e., Evans and Lyons assume that foreign- and domestic-currency assets are not perfect substitutes.) This is a key assumption: it makes room in the model for portfolio-balance effects on price. Consistent with negative exponential utility, the public's total demand for foreign exchange in round-3, denoted  $C_t^3$ , is a linear function of its expected return conditional on public information:

$$(7) \quad C_t^3 = gE\left[\Delta P_{t+1}^3 + R_{t+1} \mid \Omega_t^3\right]$$

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<sup>15</sup> This is tantamount to assuming that—when it comes to bearing overnight risk—the dealers' capacity is small relative to the capacity of the whole public.

The positive coefficient  $\gamma$  captures the aggregate risk-bearing capacity of the public: a larger  $\gamma$  means the public is willing to absorb a larger foreign-exchange position for a given expected return.  $\Omega_t^3$  is the public information available at the time of trading in round 3 (which includes all past  $R_t$  and  $X_t$ ).

### **The Pricing Relation**

Evans and Lyons (1999) show that the price at the end of day  $t$  is:

$$(8) \quad P_t = b_1 \sum_{t=1}^t \Delta R_t + b_2 \sum_{t=1}^t X_t$$

The change in price from the end of day  $t-1$  to the end of day  $t$  can therefore be written as:

$$(9) \quad \Delta P_t = b_1 \Delta R_t + b_2 X_t$$

where  $\beta_2$  is a positive constant (that depends on  $\gamma$  and  $\alpha$ ).<sup>16</sup> It is not surprising that this price change includes the payoff increment  $\Delta R_t$ : upon realization, the increment  $\Delta R_t$  becomes a known (i.e., risk-free) component of the continuing daily payoff  $R_t$ , and its discounted value is impounded in price ( $\beta_1$ ).

Let me provide some intuition for the portfolio-balance effect—the  $\beta_2 X_t$  term. This term is the required price adjustment that induces re-absorption of the random order flow  $C_t^1$  that occurred at the beginning of the day. The value of the parameter  $\beta_2$  insures that at the round-3 price,

$$C_t^1 + C_t^3 = 0$$

i.e., that the dealers have no net overnight position. To understand the link to order flow, recall that the round-3 price depends on two things: the public's risk-bearing capacity (summarized by  $\gamma$ ), and the total position that the public needs to absorb. As noted, dealers learn about the total position the public needs to absorb from order flow  $X_t$ . This produces the relation between the interdealer order flow and the subsequent price adjustment.

Let's walk through an example. Consider the price at the close of day  $t$ , as described by equation (8). The next day's increment to the daily payoff  $R$ ,  $\Delta R_{t+1}$ , is uncertain, but all previous realizations of the payoff increment  $\Delta R$  are known and are impounded in price. (Expectations of future realizations do not enter equation 8 due to the simple specification of  $\Delta R_t$  and  $C_t^1$  as independently distributed across time with mean zero.) To understand the portfolio-balance term,  $\beta_2 \sum_t X_t$ , recall that:

$$X_t \equiv \sum_{i=1}^N T_{it} = a C_t^1$$

Therefore, we can write:

$$\sum_{t=1}^t X_t \propto \sum_{t=1}^t C_t^1$$

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<sup>16</sup> This model can also be used to generate multiple equilibria. Introducing multiple equilibria obscures the essential portfolio-balance logic, however, so I do not pursue this direction here.

The sum of the portfolio shifts  $C_t^1$  represent changes in “effective” asset supply, in the sense that shifts out of FX are an increase in the net supply that the remainder of the public must absorb. (I couch this in terms of supply to connect with traditional portfolio balance intuition.) The total increase in net supply is the sum of past portfolio shifts out of FX,

$$\text{Increase in net supply} = - \sum_{t=1}^t C_t^1$$

As is standard in portfolio balance models, increases in supply lower price, and decreases in supply raise price. This is why a negative cumulative  $X_t$  in equation (8) lowers price: if cumulative  $X_t$  is negative, this implies that cumulative  $C_t^1$  is also negative, which is an increase in net supply, requiring a decrease in price to clear the market.  $X_t$  is the variable that conveys this information about the decrease in net supply ( $C_t^1$  is unobservable).  $P_t$  depends on the sum of the  $X_t$  because each additional decrease in supply  $C_t^1$  requires a *persistent* incremental increase in price.

Before moving on to the Evans-Lyons results, I want to address another of their model’s important features. Recall that one of their modeling objectives is to clarify the behavior of order flow in figure 3. Specifically, cumulative order flow is puzzlingly persistent: there is no obvious evidence of mean reversion in cumulative order flow, yet, empirically, individual dealer inventories have a short half-life. How can these two facts be consistent? The Evans-Lyons model provides an explanation. First, note that dealer inventories in the Evans-Lyons model are short-lived: no dealer carries an inventory longer than one day. At the same time, cumulative interdealer order flow in their model is persistent—in fact, it follows a random walk (i.e., there is no mean reversion whatsoever). Equations (5) and (6) hold the key to this random-walk result. Interdealer order flow each day is proportional to the public order flow that occurs at the beginning of that day. Because this public order flow is i.i.d. across dealers and time, cumulative interdealer order flow follows a random walk. In the end, these seemingly incongruous facts are consistent because, ultimately, dealers can only decumulate inventory by trading with the public, so aggregate decumulation is not reflected in interdealer flow.<sup>17</sup>

## **Evans-Lyons Results**

The equation Evans and Lyons actually estimate is the following:

$$(10) \quad \Delta p_t = \beta_0 + \beta_1 \Delta(i_t - i_t^*) + \beta_2 X_t + \eta_t$$

where  $\Delta p_t$  is the change in the log spot rate (DM/\$ or ¥/\$) from the end of day  $t-1$  to the end of day  $t$ ,  $\Delta(i_t - i_t^*)$  is the change in the overnight interest differential from day  $t-1$  to day  $t$  (\* denotes DM or ¥), and  $X_t$  is the interdealer order flow from the end of day  $t-1$  to the end of day  $t$  (negative denotes net dollar sales).

There are two changes in this equation relative to equation (9). First, the public-information payoff  $\Delta R_t$  in equation (9) represents the macro component, or  $f(i, m, z)$ . To estimate the model, Evans and Lyons have to take a stand on what to include in the regression for  $\Delta R_t$ . They choose to include changes in the nominal

<sup>17</sup> Consider an example. Starting from  $X_t=0$ , an initial customer sale to a dealer does not move  $X_t$  from zero because  $X_t$  measures interdealer order flow only. After the customer sale (say of one unit), then when dealer  $i$  unloads the position by selling to another dealer, dealer  $j$ ,  $X_t$  drops to  $-1$ . A subsequent sale by dealer  $j$  to another dealer, dealer  $k$ , reduces  $X_t$  further to  $-2$ . If a customer happens to buy dealer  $k$ ’s position from him, then the process comes to rest with  $X_t$  at  $-2$ . In this simple scenario, order flow measured only from trades between customers and dealers would have reverted to zero: the concluding customer trade offsets the initiating customer trade, putting a stop to the hot potato. The interdealer order flow, however, does not revert to zero.

interest differential; i.e., they define  $\Delta R_t = \Delta(i_t - i_t^*)$ , where  $i_t$  is the nominal dollar interest rate and  $i_t^*$  is the nominal non-dollar interest rate (DM or Yen). As a measure of variation in macro fundamentals, the interest differential is obviously incomplete. The reason Evans and Lyons do not specify a full-blown macro model is because other macro variables (e.g., money supply, output, etc.) are not available at the daily frequency. Accordingly, one should not view their model as fully accommodating both the macro and micro approaches. At the same time, if one were to choose a single macro determinant that needs to be included, interest rates would be it: innovations in interest differentials are the main engine of exchange-rate variation in macro models (e.g., the sticky-price monetary model).<sup>18</sup> Moreover, using the change in the interest differential rather than the level is consistent with monetary macro models: in monetary models, shocks to price are driven by unanticipated changes in the differential.<sup>19</sup>

The second difference in equation (10) relative to (9) is the replacement of the change in price  $\Delta P_t$  with the change in the log price  $\Delta p_t$ . This difference makes their estimation more directly comparable to previous macro specifications, since those specifications use the log change (which is approximately equal to a percentage change). As an empirical matter, using  $\Delta p_t$  is inconsequential: the two different measures for the change in price produce nearly identical results.

Table 1 presents estimates of the Evans-Lyons model (equation 10) using daily data for the DM/\$ and ¥/\$ exchange rates. The coefficient  $\beta_2$  on order flow  $X_t$  is correctly signed and significant, with t-statistics above 5 in both equations. To see that the sign is correct, recall from the model that net purchases of dollars—a positive  $X_t$ —should lead to a higher DM price of dollars. The traditional macro-fundamental—the interest differential—is correctly signed, but is only significant in the yen equation. (The sign should be positive because, in the sticky-price monetary model for example, an increase in the dollar interest rate  $i_t$  induces an immediate dollar appreciation—increase in DM/\$.)

The overall fit of the model is striking relative to traditional macro models, with  $R^2$  statistics of 64 percent and 45 percent for the DM and yen equations, respectively. Moreover, the explanatory power of these regressions is almost wholly due to order flow  $X_t$ : regressing  $\Delta p_t$  on  $\Delta(i_t - i_t^*)$  alone, plus a constant, produces an  $R^2$  statistic less than 1 percent in both equations, and coefficients on  $\Delta(i_t - i_t^*)$  that are insignificant at the 5 percent level.<sup>20</sup> That the interest differential regains significance once order flow is included, at least in the Yen equation, is consistent with omitted variable bias in the interest-rates-only specification.

The size of the order flow coefficient is consistent with estimates based on single-dealer data. The coefficient of 2.1 in the DM equation of table 1 implies that a day with 1000 more dollar purchases than sales induces an increase in the DM price by 2.1 percent. Given an average trade size in the sample of \$3.9 million, this implies that:<sup>21</sup>

- \$1 billion of net dollar purchases increases the DM price of a dollar by 0.54%.

<sup>18</sup> Cheung and Chinn (1999b) corroborate this empirically: their surveys of foreign exchange traders show that the importance of individual macroeconomic variables shifts over time, but “interest rates always appear to be important.”

<sup>19</sup> As a diagnostic, though, Evans and Lyons also estimate the model using the *level* of the differential, *a la* Uncovered Interest Parity, and find similar results.

<sup>20</sup> There is a vast empirical literature that attempts to increase the explanatory power of interest rates in exchange rate equations (by introducing individual interest rates as separate regressors, by introducing non-linearities, etc.). Because these efforts have not been successful, it is very unlikely that variations on the interest rate specification could alter the relative importance of order flow.

<sup>21</sup> One of the shortcomings of the Evans (1997) data set is that it does not include the size of each trade, so that order flow is measured as the number of buys minus the number of sells. (The data set does include the total volume over the sample, however, so that an average trade size can be calculated.) This shortcoming must be kept in perspective, however: if the Evans-Lyons results were negative, then data concerns would be serious indeed—the negative results could easily be due to noisy data. But their results are quite positive, which noise alone could not produce. Indeed, that there is noise in the data only underscores the apparent strength of the order-flow/price relation.

Equivalently, at a spot rate of 1.5 DM/\$, \$1 billion of net dollar purchases increases the DM price of a dollar by 0.8 pfennig. Turning now to estimates at the single-dealer level, these show that information asymmetry induces the dealer to increase price by  $1/100^{\text{th}}$  of a pfennig (0.0001 DM) for every incoming buy order of \$10 million (Lyons 1995). That translates to 1 pfennig per \$1 billion, versus the 0.8 pfennig per \$1 billion found by Evans and Lyons. Though linearly extrapolating the single-dealer estimate (based on individual order sizes around \$10 million) to \$1 billion of order flow is certainly not an accurate description of single-dealer price elasticity, with multiple dealers it may be a good description of price elasticity marketwide.

## **Robustness Checks**

To check robustness, Evans and Lyons examine several obvious variations on the model.<sup>b</sup> For example, they include a constant in the regression, even though the model does not call for one; the constant is insignificant for both currencies and has no substantive effect on the other coefficients. Second, in the spirit of Uncovered Interest Parity, they include the level of the interest differential in lieu of its change; the level of the differential is insignificant in both cases. Third, they test for simple forms of non-linearity, such as adding a squared order-flow term, or testing for piece-wise linearity. Though the squared order-flow term is insignificant in both equations, and they find no evidence of piece-wise linearity in the DM equation, they do find some evidence of piece-wise linearity in the Yen equation (there is a greater sensitivity of the ¥/\$ price to order flow in the downward direction, though estimates for both directions are positive and significant). Fourth, they test whether the order-flow/price relation depends on the gross level of activity. They find that it does: in the DM equation, the order-flow coefficient is lowest on days when the number of transactions is at a middling level (i.e., the pattern is U-shaped); in the Yen equation, they find that the order-flow coefficient is lowest on days when the number of transactions are at a low level (i.e., the coefficient increases with activity level). Their model is not rich enough to account for these coefficient variations. Fifth, Evans and Lyons decompose contemporaneous order flow into expected and unexpected components (by projecting order flow on past flow). In their model, all order flow  $X_t$  is unexpected, but this need not be the case in the data. They find, as one would expect, that order flow's explanatory power comes from its unexpected component.

## **Isn't This Just Demand Increases Driving Price Increases?**

At first blush, it might appear that the Evans-Lyons results are right out of Economics 101: of course when demand goes up, price goes up. But this misses the most important lesson. A premise of textbook exchange-rate models is that we don't need order flow to push prices around. Rather, when public information arrives, rational markets adjust price instantaneously (i.e., excess demand from new information causes price to adjust without trading needing to take place). That order flow explains such a large percentage of price moves underscores the inadequacy of this public-information framework. The information the FX market is aggregating is much subtler than textbook models assume. This we learn from our order flow regressions.

## **But What Drives Order Flow?**

An important challenge for the microstructure approach is determining what drives order flow, i.e., the first link in the fundamentals/order-flow/price chain (Figure 2). Here are three promising strategies for shedding light on this question. Strategy one is to disaggregate order flow. For example, interdealer order flow can be split into large banks versus small banks, or investment banks versus commercial banks. Data sets on customer order flow can be split into non-financial corporations, leveraged financial institutions (e.g.,

hedge funds), and unleveraged financial institutions (e.g., mutual and pension funds). Do all these trade types have the same price impact? Someone believing that order flow is just undifferentiated demand would predict that they do. In fact, they do not: certain types of orders (e.g., those from financial institutions) convey more information, and therefore have more price impact. People who view order flow as undifferentiated demand overlook this level of analysis, i.e., they overlook the fact that order flow is a vehicle for conveying information. Understanding the information intensity of different trade types brings us closer to this market's underlying information structure.

Strategy two for determining what drives order flow focuses on public information intensity. Consider, for example, periods encompassing scheduled macro announcements. Does order flow account for a smaller share of the price variation within these periods? Or is order flow an important driver of price even at these times, perhaps helping to reconcile differences in people's mapping from public information to price? Work along these lines, too, will shed light on the forces driving order flow.<sup>22</sup>

Strategy three for determining what drives order flow focuses on discriminating payoff information from discount-rate information. If order flow conveys payoff information, then it should forecast surprises in important macro variables like interest rates, money supplies, and trade balances. New order-flow data sets that cover many years of FX trading—such as that used by Fan and Lyons (2001)—provide enough statistical power to test this. At a broad level, separating these two types of non-public information has implications for how we define the concept of “fundamentals.” Order flow that reflects information about payoffs—like expectations of future interest rates—is in keeping with traditional definitions of exchange-rate fundamentals. But order flow that reflects changing discount rates may encompass nontraditional exchange-rate determinants (e.g., changing risk preferences, or changing hedging demands), calling perhaps for a broader definition.

### **Comments on Causality**

Under the Evans-Lyons model's null hypothesis, causality runs strictly from order flow to price. Accordingly, under the null, their estimation is not subject to simultaneity bias. (Unlike the classic supply-demand identification problem, Evans and Lyons are not simply regressing price on quantity; quantity—i.e., volume—and order flow are fundamentally different concepts.) Within microstructure theory more broadly, this direction of causality holds in all the canonical models (i.e., the Kyle auction model and the sequential-trade model), despite the fact that price and order flow are determined simultaneously. In these models, price innovations are a function of order flow innovations, not the other way around. Put differently, order flow is indeed a cause of price changes, but only a proximate cause; the underlying cause is non-public information (about payoffs or about discount rates).

Although there is no simultaneity bias under the null hypothesis, alternative hypotheses do exist under which causality is reversed. Let me offer a few thoughts. First, in the FX market there is no momentum in daily returns, so it is difficult to rationalize momentum (i.e., feedback) trading strategies in this context. Second, work by Killeen et al. (2001) shows that daily FX order flow Granger causes returns, but not vice versa. Finally, even in episodes where one would expect feedback trading, e.g., when institutions are distressed, the evidence is not there. The best example of this is the recent experience of October 1998 in the dollar/yen market (after collapse of the hedge fund Long Term Capital Management). The dollar fell from about 130 ¥/\$ to about 118 ¥/\$ *in a single day*. The popular press view of this episode was that hedge funds attempting to stop their already substantial losses felt they had to sell into a falling market, thereby making it

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<sup>22</sup> A direct role for macro announcements in determining order flow warrants exploring as well (see Evans and Lyons 2001b). Another possible use of macro announcements is to introduce them directly into an Evans-Lyons-type model. This tack is not likely to be fruitful, however: there is a long literature showing that macro announcements are unable to account for exchange rate first moments (though they do help to account for second moments—see Andersen and Bollerslev 1998 and Andersen et al. 2001).



fall further. Using data on order flows over that period, I examine this special episode as a case study in Lyons (2001). In the end, the data do not support the popular story that distressed hedge funds were rushing from the dollar en masse that day. On the contrary, they provided liquidity (i.e., they bought the dollar on that day in aggregate). The selling came from other sources.

### 3. The Excess Volatility Puzzle

This section addresses the second of the big-three puzzles: the excess volatility puzzle. By excess I mean that exchange rates are much more volatile than our best measures of fundamentals. Though other asset markets share this property (e.g., stock markets, see Shiller 1981), the puzzle in FX markets is in many ways distinctive.<sup>23</sup> Consider, for example, the fact that most exchange rates are not allowed to float freely; many are managed through intervention by central banks. This fact allows one to address the volatility puzzle in ways not possible in other markets. To understand why, note first that exchange rates are generally less volatile when managed. Given this, one can compare regimes with different management intensities to identify why volatility differs, thereby shedding light on the volatility's causes. This approach is common in the literature (e.g., Flood and Rose 1995 and Killeen, Lyons, and Moore 2000). The analysis I present here draws primarily on the empirical findings of Killeen, Lyons, and Moore (KLM).

Before reviewing the KLM findings, let me provide more perspective on the “cross-regime” approach to exchange-rate volatility.<sup>24</sup> Why is it that similar macro environments produce more volatility when exchange rates float freely? There are two main approaches to this question, one theoretical and one empirical. The theoretical approach was pioneered by Dornbusch (1976) in his sticky-price monetary model. Dornbusch shows that when goods prices are sticky, but the exchange rate is free to jump, then economic shocks have a disproportionately large effect on the exchange rate—so-called overshooting. From the perspective of excess volatility, the sticky-price monetary model generates the kind of “amplification” that might explain why floating rates are more volatile than fundamentals. This theoretical explanation is not borne out empirically, however: the sticky-price model does not fit the data.

The second main approach to why floating rates are more volatile is empirical. A good example is Flood and Rose (1995), who put the cross-regime logic as follows:

Intuitively, if exchange rate stability arises across regimes without corresponding variation in macroeconomic volatility, then macroeconomic variables will be unable to explain much exchange rate volatility. Thus existing models, such as monetary models, do not pass our test; indeed, this is also true of any potential model that depends on standard macroeconomic variables. We are driven to the conclusion that the most critical determinants of exchange rate volatility are not macroeconomic.

The central idea here starts with the Flood-Rose finding that managing rates does not change the volatility of fundamentals (fundamentals as described by the public information approach). So, if the volatility reduction from management is not coming from changed behavior of these fundamentals, then it is unlikely these are critical fundamentals. In a sense, then, the Flood-Rose conclusion deepens the puzzle.

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<sup>23</sup> Contrary to popular belief, in an absolute sense exchange rates are less volatile than stock prices: the annual standard deviation of exchange rate returns is in the 10-12 percent range for major currencies against the dollar, whereas the annual standard deviation of equity market returns is in the 15-20 percent range (and for individual stocks it is still higher).

<sup>24</sup> Exchange-rate regimes are not limited to floating and fixed. They fall along a spectrum. Ordered in terms of increasing commitment to the exchange-rate target, these regimes include: (1) free float, (2) dirty float, (3) target zone, (4) peg—fixed or crawling, (5) currency board, and (6) monetary union. A dirty float involves some limited intervention. A currency board is an institutional commitment to dedicate monetary policy to the exchange-rate target. For more on the differences between these regimes, see for example Krugman and Obstfeld (2000).

KLM take a different tack—they exploit a natural experiment. The experiment is the switch from the European Monetary System (EMS) to European Monetary Union (EMU), which in terms of regimes is a switch from a target zone to a rigidly fixed rate.<sup>25</sup> Starting in January 1999, the euro-country currencies have been rigidly fixed to one another. Before January 1999, however—particularly before May 1998—there was still uncertainty about which countries would participate in EMU. There was also uncertainty about the timing of interest-rate harmonization (which had to occur among the countries adopting the euro).

KLM’s analysis of this experiment leads them to the following punch-line: exchange rates are more volatile under flexible rates because of order flow. Order flow conveys more information under flexible rates, which increases volatility. Under fixed exchange rates, order flow is prevented from conveying information—as a driver of returns, it is “turned off.” The intuition for why this happens is tied to demand elasticity. Under floating, the elasticity of public demand is (endogenously) low, due to higher volatility and aversion to the risk this higher volatility entails. This makes room for the types of portfolio-balance effects that arise in the Evans-Lyons model, and allows order flow to convey information about those effects. Under (perfectly credible) fixed rates, the elasticity of public demand is infinite: return volatility shrinks to zero, making the holding of foreign exchange effectively riskless. This eliminates portfolio-balance effects and precludes order flow from conveying this type of information. Consequently, order flow as a return driver is shut down.

Figure 6 provides an initial, suggestive illustration of the KLM results. It shows the relationship between the FF/DM exchange rate and cumulative order flow (interdealer order flow from EBS—see below). The vertical line is 4 May 1998, the first trading day after the announcement of the conversion rates of the euro-participating currencies. The relationship between the two series before May 4<sup>th</sup> is clearly positive: the correlation is 0.69. After May 4<sup>th</sup>, however, there is a sharp unwinding of long DM positions with no corresponding movement in the exchange rate. In fact, during the second period there is a *negative* correlation of −0.35. Though total variation in the exchange rate is small, the effect of order flow on the exchange rate appears to have changed from one of clear impact to one of no impact. The model KLM develop provides a more formal framework for addressing this issue (to which I now turn).

## **Model Sketch**

The specification of trading within each day is identical to that of Evans and Lyons (1999). The key difference here is the presence of two trading regimes: a flexible-rate regime followed by a fixed-rate regime. The shift from flexible to fixed rates is a random event that arrives with constant probability  $p$  at the end of each trading day (after all trading).<sup>26</sup> Once the regime has shifted to fixed rates it remains there indefinitely.

KLM show that the resulting price level at the end of day  $t$  can be written as:

<sup>25</sup> The transition from EMS to EMU was indisputably a transition toward exchange-rate fixity. KLM assume that EMU was perfectly credible after the weekend of May 2/3, 1998—the date the eleven “in” countries were selected and the date the internal conversion rates for the euro-zone were determined. Extending their model to environments of imperfectly credible fixed rates is a natural direction for further research.

<sup>26</sup> This formulation has two important advantages. First, the effective horizon over which foreign exchange is priced in the flexible-rate regime remains constant. Second, the parameter  $p$  provides a compact means of describing regime shifts as far or near. As an empirical matter, particularly in the context of the EMS-EMU transition, this specification serves as a convenient abstraction from reality.

$$(11) P_t = \begin{cases} I_1 \sum_{t=1}^t \Delta R_t + I_2 \sum_{t=1}^t X_t & \text{under flexible rates (} t \leq T \text{)} \\ I_1 \sum_{t=1}^T \Delta R_t + I_2 \sum_{t=1}^T X_t + I_3 \sum_{t=T+1}^t X_t & \text{under fixed rates (} t > T \text{)} \end{cases}$$

where  $T$  denotes the day on which the regime shifts from flexible to fixed rates. The message of this equation is important: it describes a cointegrating relationship between the level of the exchange rate, cumulative macro fundamentals, and cumulative order flow. (This long-run relationship between cumulative order flow and the level of the exchange rate is not predicted by any traditional exchange-rate model.) The cointegrating vector is regime dependent, however.

Under flexible rates, the change in the exchange rate from the end of day  $t-1$  to the end of day  $t$  can be written as:

$$(12) \quad \Delta P_t = I_1 \Delta R_t + I_2 X_t$$

where  $I_1$  and  $I_2$  are positive constants. The portfolio-balance effects from order flow enter through  $I_2$ , which depends inversely on  $\gamma$ —the elasticity of public demand with respect to expected return—and also on the variances  $S_R^2$  and  $S_C^2$ .<sup>27</sup>

### **Differences Across Trading Regimes**

Understanding the effects of the different trading regimes—and the changing role of order flow—comes from the effect of the exchange-rate regime on equations (11) and (12). Specifically, the parameter  $\gamma$ , which represents the elasticity of public demand, is regime-dependent. This comes from the regime-dependence of the return variance  $\text{Var}[\Delta P_{t+1} + R_{t+1} | \Omega_t^3]$  ( $\gamma$  being proportional to the inverse of this variance). The elimination of portfolio-balance effects under fixed rates reduces this variance, implying that:

$$(13) \quad g_{\text{flexible}} < g_{\text{fixed}}$$

Public demand is therefore more elastic in the (credible) fixed-rate regime than the flexible-rate regime. The implication for the price impact parameters  $I_2$  and  $I_3$  in equation (11)—henceforth  $I_{\text{flexible}}$  and  $I_{\text{fixed}}$  respectively—is the following:

$$(14) \quad I_{\text{flexible}} > I_{\text{fixed}}$$

Thus, the exchange rate reacts more to order flow under flexible rates than under fixed rates. For perfectly credible fixed rates (i.e., for which  $\text{Var}[\Delta P_{t+1} + R_{t+1} | \Omega_t^3] = 0$ ), we have:

$$(15) \quad I_{\text{fixed}} = 0$$

The exchange rate does not respond to order flow in this case. The intuition is clear: under perfect credibility, the variance of exchange-rate returns goes to zero because public demand is perfectly elastic, and vice versa.

<sup>27</sup> The probability  $p$  of the regime shift adds a parameter to the Evans-Lyons solution that has no qualitative impact on the coefficients of interest here, namely  $\lambda_2$  and  $\lambda_3$ .

For intuition, consider  $P_{T+1}$ , the price at the close of the first day of the fixed-rate regime. Foreign exchange is a riskless asset at this point, with return variance equal to zero. A return variance of zero implies that the elasticity of the public's speculative demand is infinite, and the price impact parameter  $\lambda_3$  in equation (4) equals zero. This yields a price at the close of trading (round 3) on day T+1 of:

$$P_{T+1} = I_1 \sum_{t=1}^T \Delta R_t + I_2 \sum_{t=1}^T X_t$$

The summation over the payoff increment  $\Delta R_t$  does not include an increment for day T+1 because the central bank maintains  $\Delta R_t$  at zero in the fixed regime. Though  $X_{T+1}$  is not equal to zero, this has no effect on price because  $\lambda_3=0$ , as noted. This logic holds throughout the fixed-rate regime. Under flexible rates, the economics behind the price impact of order flow is the same as that under the Evans-Lyons model, adjusted only by the change in parameter values due to the possibility of regime switch.

### **The KLM Data Set**

The KLM data set includes daily order flow in the German mark-French franc market for one year, 1998. The data are from EBS, the electronic interdealer broking system. (EBS now accounts for nearly half of interdealer trading in the largest currencies, which translates into about a third of total trading in major currencies; the Evans-Lyons data reflect the other half of interdealer trading—the direct portion.) By KLM's estimate, their sample accounts for about 18% of trading in the DM/FF market in 1998. Daily order flow includes all orders passing through the system over twenty-four hours starting at midnight GMT (weekdays only).

The data set is rich enough to allow measurement of order flow  $X_t$  two ways: number of buys minus number of sells (a la Evans and Lyons 1999) and amount bought minus amount sold (in DM). KLM find that the two measures behave quite similarly: the correlation between the two  $X_t$  measures in the flexible-rate portion of the sample (the first four months) is 0.98. They also find that substituting one measure for the other in their analysis has no substantive effect on their findings.

Let me provide a bit more detail on EBS. As noted, EBS is an electronic broking system for trading spot foreign exchange among dealers. It is limit-order driven, screen-based, and ex-ante anonymous (ex-post, counter-parties settle directly with one another). The EBS screen displays the best bid and ask prices, together with information on the cash amounts available for trading at these prices. Amounts available at prices other than the best bid and offer are not displayed. Activity fields on this screen track a dealer's own recent trades, including price and amount, as well as tracking the recent trades executed on EBS system-wide.

There are two ways that dealers can trade currency on EBS. Dealers can either post prices (i.e., submit "limit orders"), which does not insure execution, or dealers can "hit" prices (i.e., submit "market orders"), which does insure execution. To construct a measure of order flow, trades are signed according to the direction of the latter—the initiator of the transaction.

When a dealer submits a limit order, she is displaying to other dealers an intention to buy or sell a given cash amount at a specified price.<sup>28</sup> Bid prices (limit order buys) and offer prices (limit order sells) are submitted with the hope of being executed against the market order of another dealer—the "initiator" of the trade. To be a bit more precise, not all initiating orders arrive in the form of market orders. Sometimes, a dealer will submit a limit-order buy that is equal to or higher than the current best offer (or will submit a limit-order sell that is equal to or lower than the current best bid). When this happens, the incoming limit

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<sup>28</sup> EBS has a pre-screened credit facility whereby dealers can only see prices for trades that would not violate their counterparty credit limits, thereby eliminating the potential for failed deals because of credit issues.

order is treated as if it were a market order, and is executed against the best opposing limit order immediately. In these cases, the incoming limit order is the initiating side of the trade.

## **Results**

The relationship between cumulative order flow and the exchange rate is illustrated above in figure 5. We saw that the effect of order flow on the exchange rate appears to have changed from one of clear impact to one of no impact. The results that follow address this more formally, based on the KLM model's testable implications.

The analysis proceeds in two stages. First, KLM address whether there is evidence of a cointegrating relationship between order flow and price, as the model predicts. This first stage also examines the related issues of stationarity and long-run coefficient sizes. The second stage addresses the degree to which order flow is exogenous (as assumed in their model). This stage includes a test for reverse Granger causality, i.e., statistical causality running from the exchange rate to order flow.

### **Stage 1: Cointegration and Related Issues**

Let us begin by repeating equation (11) from the model, which establishes the relationship between the level of the exchange rate  $P_t$ , a variable summarizing public information ( $\Sigma \Delta R_t$ ), and accumulated order flow ( $\Sigma X_t$ ).

$$(11) \ P_t = \begin{cases} I_1 \sum_{t=1}^t \Delta R_t + I_2 \sum_{t=1}^t X_t & \text{under flexible rates (t} \leq T \text{)} \\ I_1 \sum_{t=1}^T \Delta R_t + I_2 \sum_{t=1}^T X_t + I_3 \sum_{t=T+1}^t X_t & \text{under fixed rates (t} > T \text{)} \end{cases}$$

Like Evans and Lyons (1999), KLM use the interest differential as the public-information variable (the Paris interbank offer rate minus the Frankfurt interbank offer rate).

The KLM model predicts that before May 4 1998, all these variables are non-stationary and are cointegrated. After May 4, the model predicts that the exchange rate converges to its conversion rate, and should be stationary. During this latter period (May to December), therefore, equation (11) only makes sense if the price-impact coefficient,  $\lambda$ , goes to zero (as the model predicts), or if accumulated order flow becomes stationary. Otherwise, the regression is unbalanced, with some stationary variables, and some non-stationary variables.

### **Stationarity**

The first step is to test whether the relevant variables are non-stationary. KLM find that in the first four months of 1998, all variables are indeed non-stationary (inference based on Dickey-Fuller tests). In the remaining eight months, the exchange rate is stationary, as expected, but both cumulative order flow and the interest differential remain non-stationary. These results are consistent with a price impact parameter  $\lambda_2$  in the latter period of zero. It is important to determine, however, whether equation (11) actually holds for the January-April period, i.e., whether the variables are cointegrated, as the model predicts.

## **Cointegration**

KLM use the Johansen procedure to test for cointegration (Johansen 1992). The unrestricted vector autoregression (VAR) is assumed to consist of the three variables—the exchange rate, cumulative order flow, and the interest differential—as well as a constant and a trend. After testing various possible lag lengths, KLM find evidence that a lag length of one is appropriate.

The cointegration tests show that there is indeed one cointegrating vector. (The null of no cointegrating vectors is rejected in favor of the alternative of at least one cointegrating vector. But the null of one cointegrating vector cannot be rejected in favor of the alternative of at least two.) This implies that a linear combination of the three variables is stationary, as the KLM model predicts.

KLM go one step further and implement the test for cointegration without the interest differential. They find evidence of one cointegrating vector in that case, too, now between the exchange rate and cumulative order flow. The finding of one cointegrating vector in both the bivariate and trivariate systems suggests that the interest differential enters the trivariate cointegrating vector with a coefficient of zero. When KLM estimate the parameters of the cointegrating vector directly, this is exactly what they find: they cannot reject that the interest differential has a coefficient of zero. By contrast, the coefficient on cumulative order flow is highly significant and correctly signed. (The size of the coefficient implies that a 1% increase in cumulative order flow moves the spot rate by about five basis points.<sup>29</sup>) These findings of cointegration and an order-flow coefficient that is correctly signed are supportive of their model's emphasis on order flow, even in the long run. At the same time, the lack of explanatory power in the interest differential suggests that this specialization of the payoff increment  $R_t$  is deficient (in keeping with the negative results of the macro literature more generally).

## **Exogeneity of Order Flow**

An important question facing the microstructure approach is the degree to which causality can be viewed as running strictly from order flow to the exchange rate, rather than running in both directions. The KLM framework provides a convenient way to address this question. In particular, if a system of variables is cointegrated, then it has an error-correction representation (see Engle and Granger 1987). These error-correction representations provide clues about the direction of causality. Specifically, the error-correction representation allows one to determine whether the burden of adjustment to long-run equilibrium falls on the exchange rate, on cumulative order flow, or both. If adjustment falls at least in part on order flow, then order flow is responding to the rest of the system (i.e., it is not exogenous in the way specified by the Evans-Lyons and KLM models).

The KLM findings suggest that causality is indeed running strictly from order flow to price, and not the other way around. KLM test this by estimating the error-correction term in both the exchange rate and order flow equations. They find that the error-correction term is highly significant in the exchange-rate equation, whereas the error-correction term in the order-flow equation is insignificant. This implies that adjustment to long-run equilibrium is occurring via the exchange rate. More intuitively, *when a gap opens in the long-run relationship between cumulative order flow and the exchange rate, it is the exchange rate that adjusts to reduce the gap, not cumulative order flow*. In the parlance of the literature, the insignificance of the error-correction term in the order-flow equation means that order flow is weakly exogenous. Further, KLM show that there is no evidence of Granger causality running from the exchange rate to order flow (i.e., feedback trading is not taking place). This combination of weak exogeneity and absence of Granger causality implies

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<sup>29</sup> In their sample, the mean value of cumulative order flow is DM1.38 billion.

that cumulative order flow is strongly exogenous. Finally, the KLM error-correction estimates suggest that about 1/3 of departures from long-run equilibrium is dissipated each day.

To summarize, the KLM analysis addresses the excess volatility puzzle on two fronts, one theoretical and one empirical. On the theoretical front, they provide a new approach—based on order flow—for why volatility is high when exchange rates float freely. The punch-line of their approach is that an important source of volatility is order flow, or, more precisely, the information order flow conveys. Under floating, the elasticity of public demand is (endogenously) low, due to higher volatility and aversion to the risk that higher volatility entails. This makes room for the portfolio-balance effects that arise in the Evans-Lyons model, and allows order flow to convey information about those effects. Under (perfectly credible) fixed rates, the elasticity of public demand is infinite: return volatility shrinks to zero, making the holding of foreign exchange effectively riskless. This eliminates portfolio-balance effects and precludes order flow from conveying this type of information. Thus, under fixed rates, order flow as a return driver is shut down.

A nice feature of the KLM approach to excess volatility, relative to other approaches, is that its implications can be brought to the data. There are many fine theoretical papers on excess exchange-rate volatility (see, e.g., Hau 1998 and Jeanne and Rose 1999, and references to earlier work contained therein). But in general little of the existing theoretical work is easily implemented empirically. The order-flow focus of the KLM approach makes it readily implementable. That said, the specific results that KLM offer are only suggestively supportive of their particular story. Much more empirical analysis along these lines remains to be done.

Two of the KLM empirical findings are especially relevant to interpreting work on order flow more generally. First, they find that Granger causality runs from order flow to the exchange rate, but not vice versa. True, Granger causality is not the same as economic causality. Nevertheless, the result does help assuage concern. Second, they find that gaps in the relationship between cumulative order flow and the level of the exchange rate engender an exchange-rate response but not an order-flow response. This result, too, helps assuage concern about the direction of causality between these two variables.

One might be tempted to conclude that four months of data is too little to produce reliable analysis of cointegration. An important aspect of the KLM results should assuage this concern, however. Recall that KLM find rapid adjustment back to the cointegrating relationship (their error-correction estimates suggest that about 1/3 of departures from long-run equilibrium is dissipated each day). The half-life of these departures is therefore only about two days. Four months of data is enough to cover about 45 of these half lives, quite a lot in the context of estimating cointegrating relationships. For comparison, estimates of adjustment back to the cointegrating relationship of Purchasing Power Parity generate half lives around 5 years. One would need over 200 years of data to estimate PPP error correction with as many half-lives in the sample.

Finally, note that the KLM model provides a different perspective on exchange-rate credibility. In their model, a credible fixed rate is one in which the private sector, not the central bank, willingly absorbs innovations in order flow.<sup>30</sup> The textbook treatment of fixed-rate regimes, in contrast, is centered on the willingness of the central bank to buy and sell domestic currency at a predetermined price; i.e., it is the central bank that absorbs the order flow. If the central bank needs to intervene, the fixed exchange-rate regime is already in difficulty because the private sector's demand for order flow is no longer perfectly elastic. It may be useful to revisit currency crises and our analysis of them with this possibility in mind.

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<sup>30</sup> This is a theoretical point. Empirically, it appears that there was little intervention by the national central banks or the ECB in the period from May to December, 1998 (these banks are not terribly forthcoming with intervention data over this period).

## 4. Conclusion

I have argued that abstracting from information aggregation when analyzing exchange rates misses quite a lot. The argument commonly offered in support of this abstraction—that dispersed information is rapidly summarized in public macro variables—is increasingly untenable. The abstraction would be easier to defend if either (1) both the public and dispersed information approaches performed well empirically or (2) both approaches performed poorly. In reality, the dispersed information approach performs rather well while the public information approach does not.

How, specifically, can one identify the information that determines order flow? The notion of order flow as an intermediate link between information and price suggests several strategies for answering this question, all of which are part of ongoing research. Three in particular are outlined here.

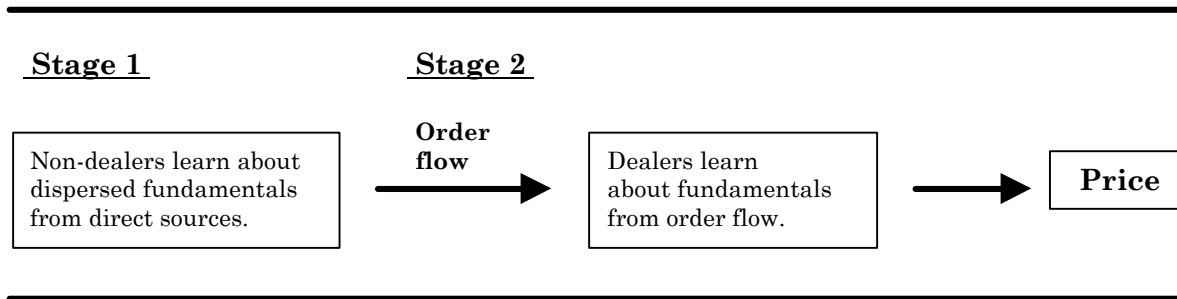
One strategy for linking order flow to underlying determinants starts by decomposing order flow. (That it can be decomposed is one of its nice properties.) Fan and Lyons (2001) test whether all parts of the aggregate order flow have the same price impact. They do not: the price impact of FX orders from financial institutions (e.g., mutual funds and hedge funds) is significantly higher than the price impact of orders from non-financial corporations. This suggests that order flow is not just undifferentiated demand. Rather, the orders of some participants are more informative than the orders of others. Analyzing order flow's parts gives us clues as to the underlying information structure.

A second strategy for linking order flow to underlying determinants is based on the view that order flow measures individuals' changing expectations. As a measure of expectations, it reflects a willingness to back one's beliefs with money—the backed-by-money expectational votes, if you will. Expectations measured from macro data, on the other hand, are slow moving and imprecise. If order flow is serving as an expectation proxy, then it should forecast surprises in important macroeconomic variables (like interest rates). New order-flow data sets that cover up to six years of FX trading provide enough statistical power to test this. Note too that this line of research offers a possible explanation of the Meese and Rogoff (1983) findings. To understand why, write the price of foreign exchange,  $P_t$ , in the standard way as a function of current and expected future macro fundamentals:  $P_t = g(f_t, f_{t+1}^e)$ . If (big if) the macro variables that order flow is forecasting are largely beyond the one-year horizon, then the empirical link between exchange rates and *current* macro variables  $f_t$  will be loose. That macro empirical results are more positive at horizons beyond one year is consistent with this “anticipation” hypothesis.

A third strategy for determining what drives order flow focuses on public information intensity. Consider, for example, periods encompassing scheduled macro announcements. Does order flow account for a smaller share of price variation within these periods? Or is order flow an important driver of price even at these times, perhaps helping to reconcile differences in people's mapping from public information to price? Work along these lines, too, will shed light on the forces driving order flow (see, e.g., Evans and Lyons 2001b).

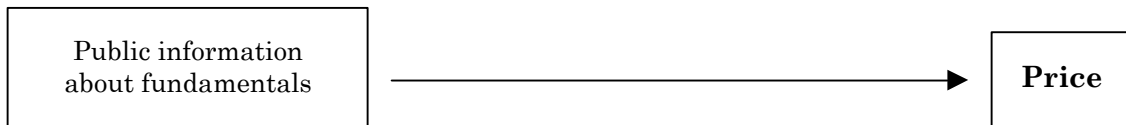


**Figure 1**  
The Two Stages of Information Processing

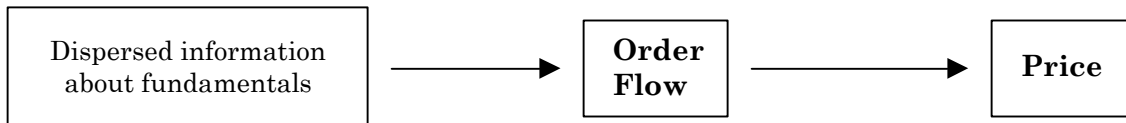


**Figure 2**  
The Two Approaches

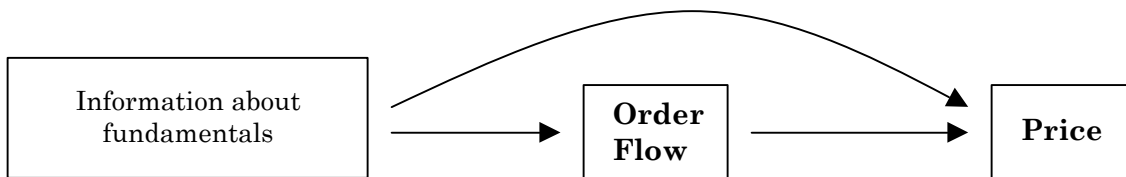
**The Public Information Approach**



**The Dispersed Information Approach**



**A Hybrid Approach**

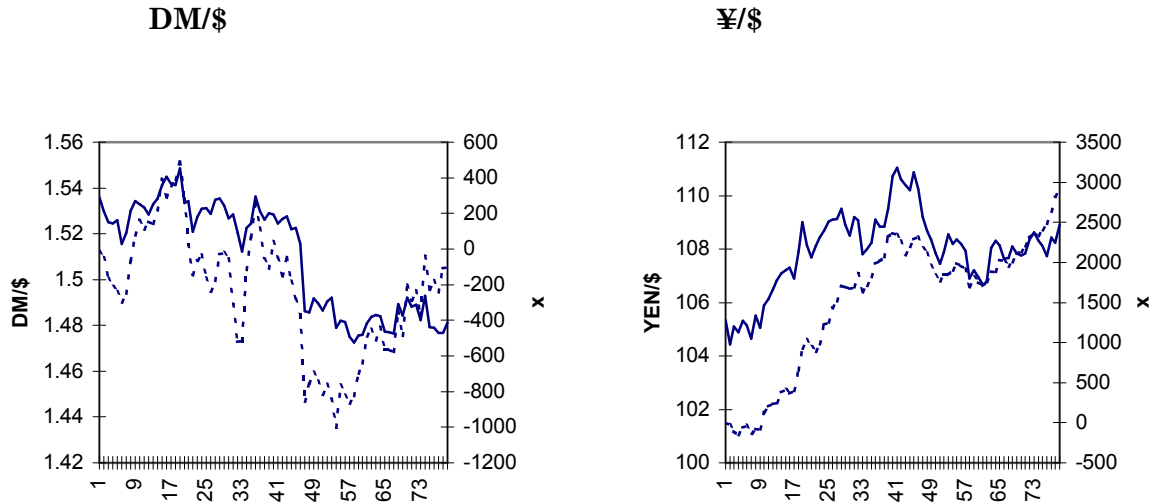



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\* The top panel illustrates the connection between fundamentals and price under the traditional macro approach: information about fundamentals is public, and so is the mapping to price, so price adjustment is direct and immediate. The middle panel shows the dispersed information approach. The focus in that case is fundamental information that is not publicly known. This type of information is first transformed into order flow, which then becomes a signal to the price setter (e.g., dealer) that price needs to be adjusted. Actual markets include both, which is illustrated in the bottom panel—the hybrid approach.

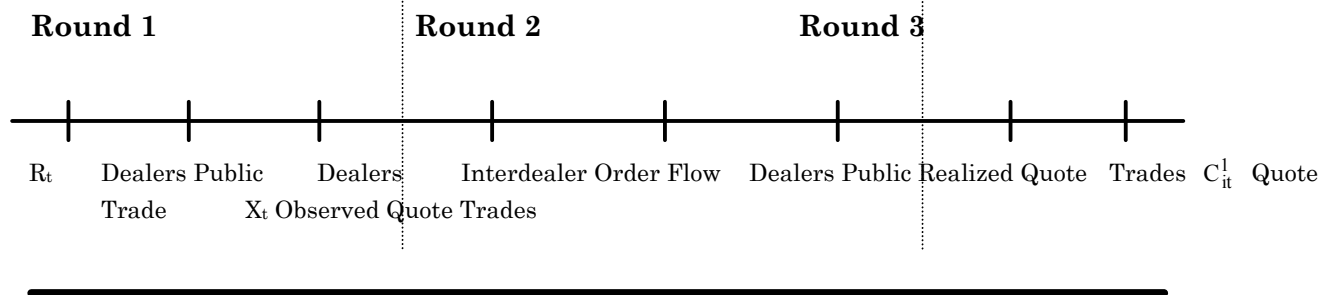
**Figure 3**

Four Months of Exchange Rates (solid) and Order Flow (dashed)  
May 1-August 31, 1996



**Figure 4**

Daily Timing in the Evans-Lyons Model



## Figure 5

### Summary of Evans and Lyons (1999) Model

- 
- |                      |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    |
|----------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Players:</b>      | <ul style="list-style-type: none"><li>▪ N dealers (risk-averse and strategic)</li><li>▪ a continuum of “customers” (risk-averse and non-strategic), whose collective risk-bearing capacity is less than infinite</li></ul>                                                                                                                                                                                                                                                                                                                                                                                                         |
| <b>Information:</b>  | <ul style="list-style-type: none"><li>▪ daily payoff <math>R_t</math> on foreign exchange is the sum of daily increments <math>\Delta R_t</math>, with each <math>\Delta R_t</math> distributed <math>\text{Normal}(0, \sigma_R^2)</math></li><li>▪ all participants observe <math>R_t</math> at the beginning of day <math>t</math></li><li>▪ in round one of each day, each dealer <math>i</math> receives a customer order <math>C_{it}^1</math>, distributed <math>\text{Normal}(0, \sigma_C^2)</math></li><li>▪ after round two of each day, all dealers observe that day’s interdealer order flow <math>X_t</math></li></ul> |
| <b>Institutions:</b> | <ul style="list-style-type: none"><li>▪ there are an infinite number of trading days</li><li>▪ each trading day, there are three rounds of trading: customer-dealer, then interdealer, then another customer-dealer</li><li>▪ dealers end each day with no net position (i.e., there are no daily frequency inventory effects)</li></ul>                                                                                                                                                                                                                                                                                           |

#### Quoting

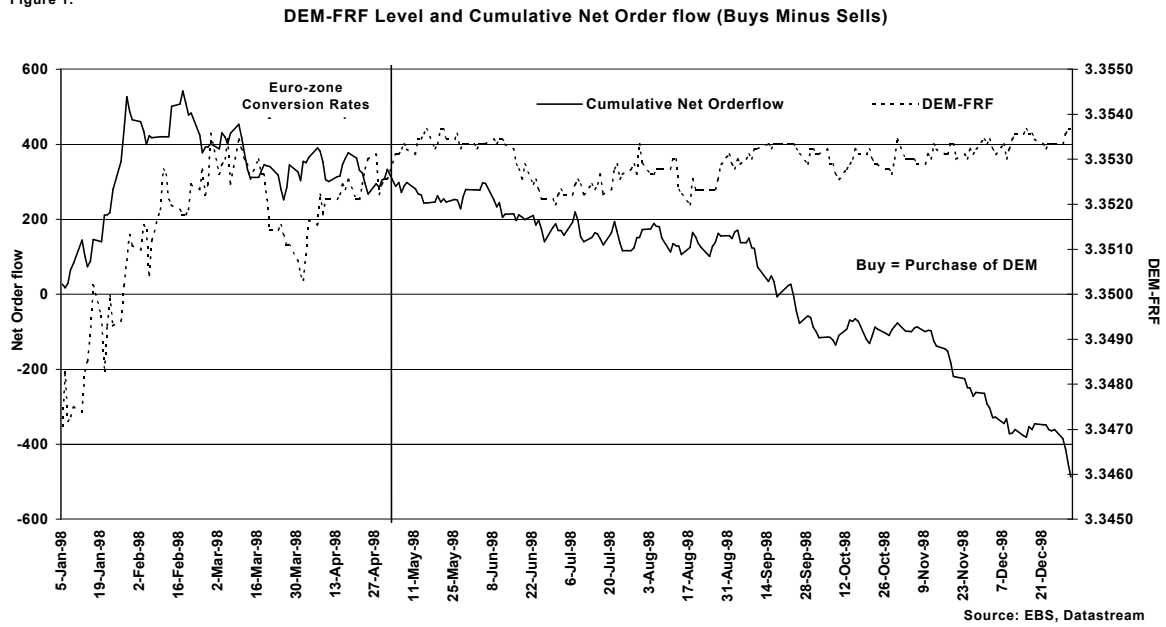
- dealer quoting is simultaneous, independent, and required
- quotes are available to all dealers
- a quote is a single price at which the dealer agrees to buy and sell any amount

#### Trading

- trading is simultaneous and independent
  - trading with multiple partners is feasible
-

# Figure 6

Figure 1.



**Table 1**  
Estimates of the Evans-Lyons model

$$\Delta p_t = \beta_0 + \beta_1 \Delta(i_t - i_t^*) + \beta_2 X_t + \eta_t$$

	$b_1$	$b_2$	$R^2$
<b>DM</b>	0.52 (1.5)	2.10 (10.5)	0.64
<b>Yen</b>	2.48 (2.7)	2.90 (6.3)	0.45

\* t-statistics are shown in parentheses (constant not reported). In the case of the DM equation, the t-statistics are corrected for heteroskedasticity; there is no evidence of heteroskedasticity in the Yen equation, and no evidence of serial correlation in either equation. The dependent variable  $\Delta p_t$  is the change in the log spot exchange rate from 4 pm GMT on day t-1 to 4 pm GMT on day t (DM/\$ or ¥/\$). The regressor  $\Delta(i_t - i_t^*)$  is the change in the one-day interest differential from day t-1 to day t (\* denotes DM or ¥, annual basis). The regressor  $X_t$  is interdealer order flow between 4 pm GMT on day t-1 and 4 pm GMT on day t (negative for net dollar sales, in thousands of transactions). Estimated using OLS. The sample spans four months (May 1 to August 31, 1996), which is 89 trading days. (Saturday and Sunday order flow—of which there is little—is included in Monday.)

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